Stochastic Downscaling for Hydrodynamic and Ecological Modeling of Lakes

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Motivation

Weather generators for hydrological modeling are around for a long time. We, however, wanted to address the quite **distinct requirements** of hydrodynamic and ecological modeling of lakes. Precipitation was not deemed important for modelling input, which allows for a simpler design compared to Semenov-type weather generators.
The requirements from downstream users were the ability to **define climate scenarios** as:

- Temperature change that propagates to the other variables.
- Random episodes of deviation from long-term day-of-year means.
- Concrete time series of temperature (from a General Circulation Model (GCM) or hand-tailored).

Two contributions to this conference use the proposed weather generator VG:

1. *"Advances in estimating the climate sensibility of a large lake using scenario simulations"* by Maria Magdalena Eder
2. *"Simulating the effect of meteorological variability on a lake ecosystem"* by Marieke Frassl

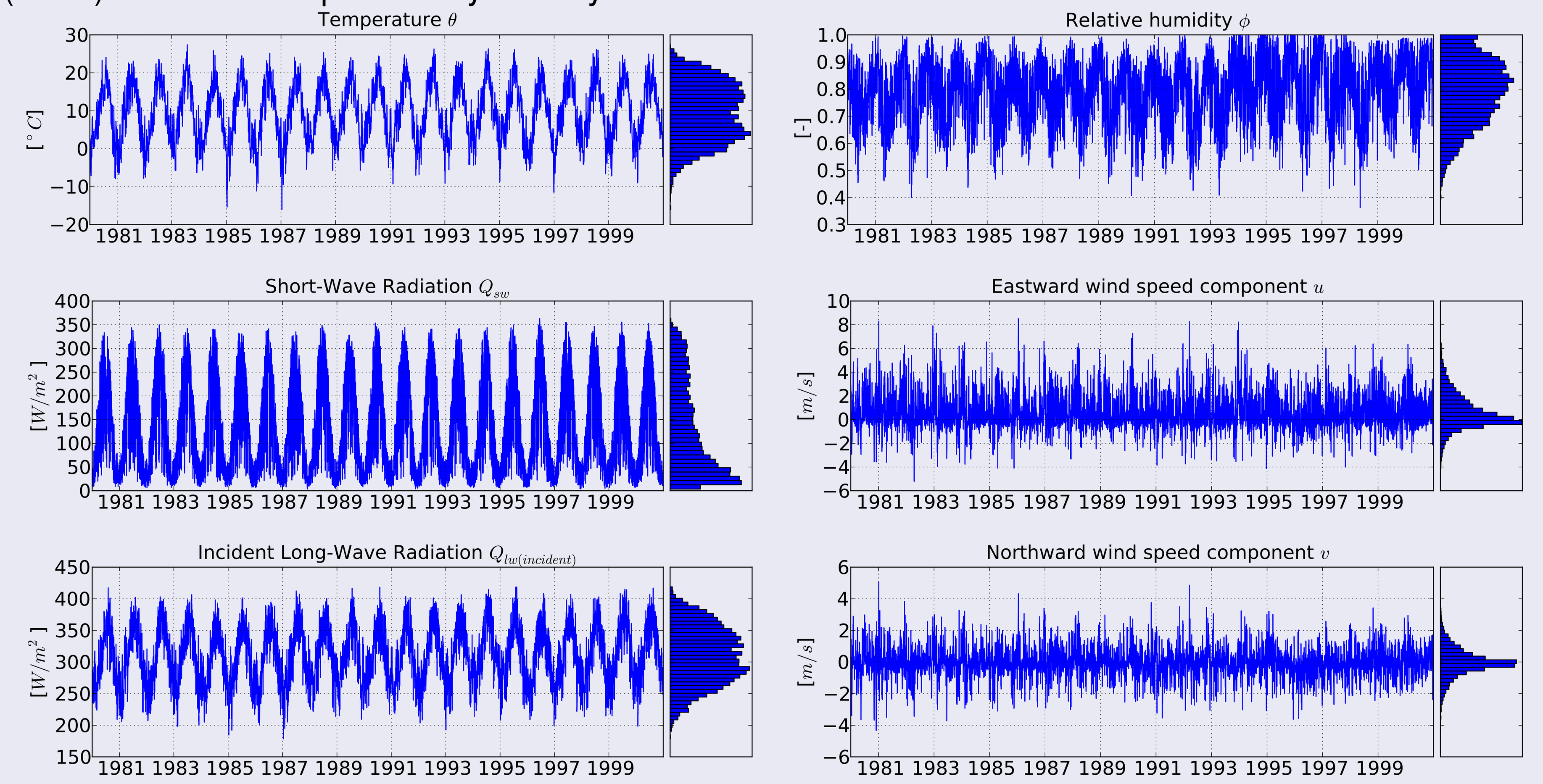
Both posters were presented in Session *"Lakes and inland seas"* (HS10.1) (Wednesday, 25 Apr 17:30-19:00). These studies showed that lake model runs using the weather generators meteorologic input variables resulted in output that was similar to those of model runs using the weather generators output. This **indirect validation** with very different models (1D and 3D) indicated that the weather generator was able to convey the relevant properties of the time series.

The Vector-Autoregressive Weather Generator (VG) modeling overview

1. Convert the input variables to standard-normal using quantile-quantile transformation.
   The parameters of theoretical distributions (temperature, long-wave radiation: normal; relative humidity: truncated normal) were described by triangular functions and fitted to the data. Short-wave radiation and the wind speed components were transformed with the help of seasonally changing kernel density estimates.
2. Fit a Vector-Autoregressive (VAR) process to the converted data
3. Simulate using the fitted VAR process with added **constant or time-varying disturbance**
4. Convert back to the fitted marginal distributions.

Meterological input data

The available data were measured hourly in Constance, Germany by the Deutscher Wetterdienst (DWD). In the subsequent analysis daily means were used.



VAR order selection and fit

The Schwartz information criterion suggested an autoregressive order of $p = 2$, the Hannan-Quinn criterion suggested $p = 4$.
$\rightarrow$ All following time series were simulated using a **VAR(p=3 days)** process.
Order selection was also done considering a Moving-Average part, but both criteria produces smaller values with $q = 0$ for any p.
u_t shows no signs of conditional heteroscedasticity effects.

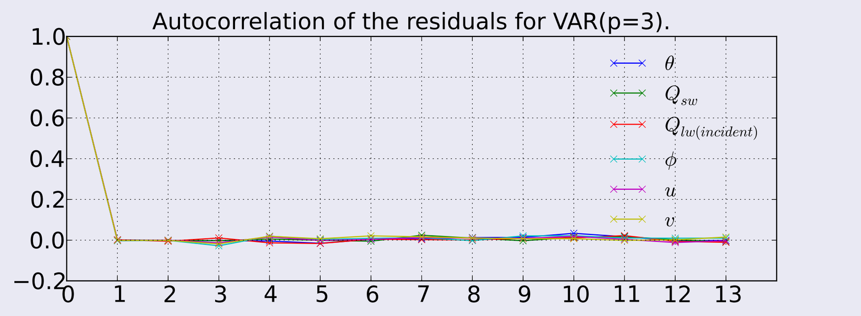


Figure : Residuals u_t show no significant autocorrelation. Hence, the VAR filter is able to capture the linear linear time dependence in the data.

Autocorrelations of measured and simulated data

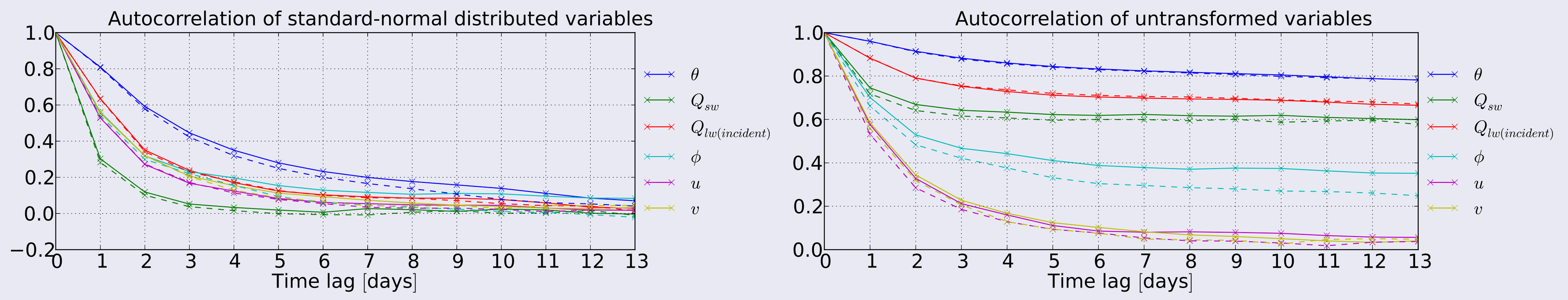


Figure : Autocorrelations. Solid lines: measured, dashed lines: simulated

Correlations of measured and simulated data

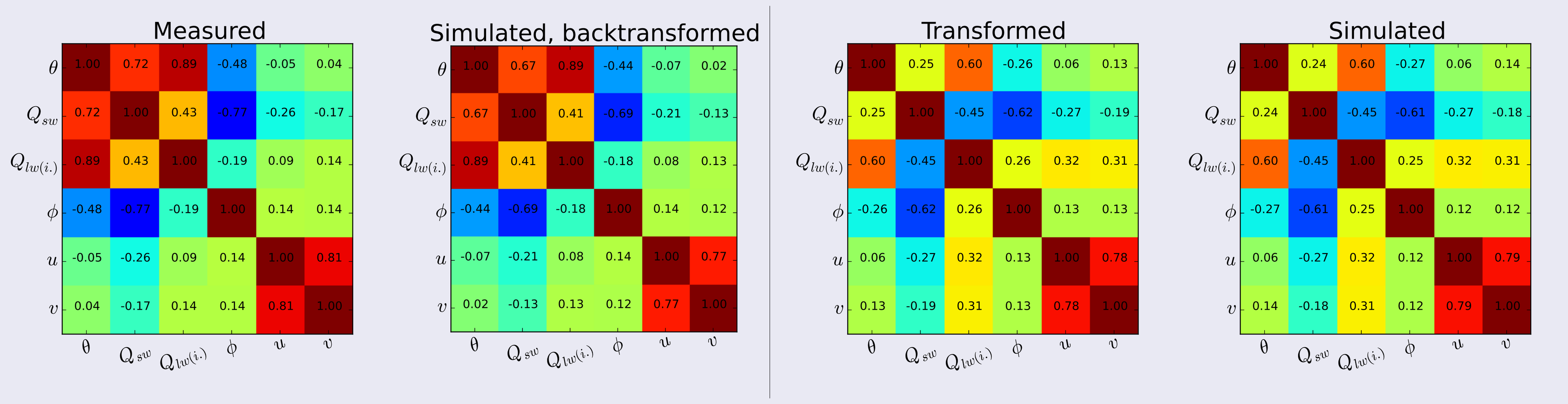
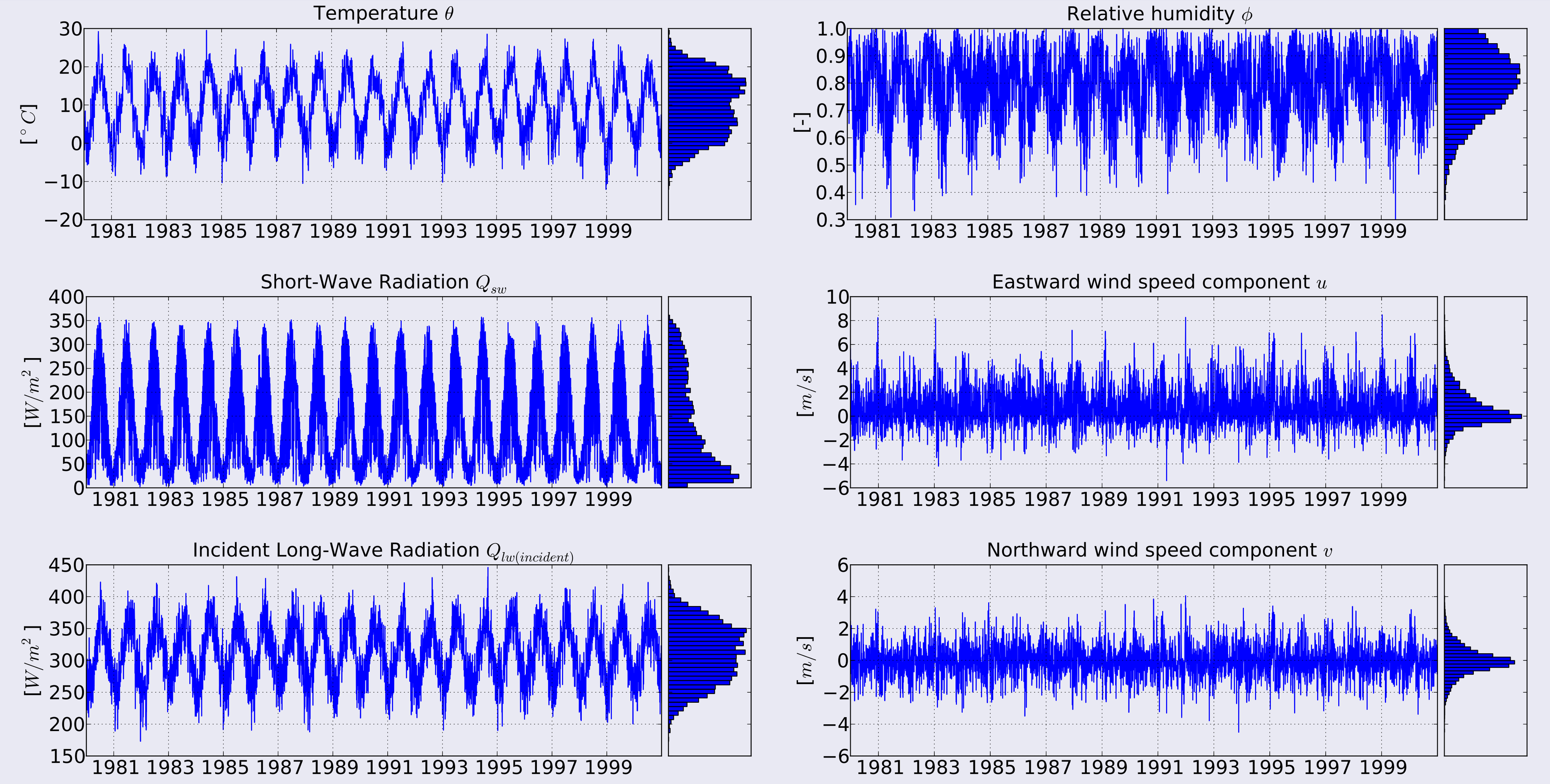


Figure : Correlation matrices for measured data, backtransformed simulated data, standard-normal transformed data and simulated data

Simulation without disturbance



Disturbing the VAR-Process

To steer the simulation one can **adjust the mean of the VAR process** by adding a disturbance vector.

$$\tilde{y}_t = A_1\tilde{y}_{t-1} + \ldots + A_p\tilde{y}_{t-p} + \tilde{u}_t + m_t \quad (1)$$

m is the added disturbance and $\tilde{u}_t$ multivariate Gaussian noise (both column-vectors of size K). A_i are $(K \times K)$ matrices that contain the parameters of the fitted VAR process.

How to get m_t?

Assuming we want to change θ (temperature) by $\Delta\theta$, first the seasonal marginal distribution has to be taken into account:

$$\Delta\theta^{std}_{doy} = \frac{\Delta\theta}{\sigma_{doy}} \quad (2)$$

This disturbance has to be further scaled by the A_i's:

$$m_{doy} = \left(I_K - \sum_{i=0}^{p} A_i\right)\Delta\bar{y}_{doy} \quad (3)$$

One of the elements of $\Delta\bar{y}_{doy}$ is $\Delta\theta^{std}_{doy}$. The other elements are estimated using a linear regression between the θ and the other variables:

$$m_i = COV\left(\theta^{std}, y_i\right) \quad (4)$$

Extracting the disturbance from a GCM

Normal distributions were fitted to the measured data and the control run of the GCM. Seasonalities were captured by describing the means and standard-deviations with triangular functions. With the help of these marginal distributions, the bias of the scenario run was then removed by **quantile-quantile transformation** resulting in the time series θ^{GCM}.
The disturbance $\Delta\theta$ is then defined as the difference of θ^{GCM}_t to the means $\bar{\theta}^{measured}_{doy}$.
$\Delta\theta$ is subsequently scaled to m^{GCM}_t using the scheme described above in "Disturbing the VAR-Process".

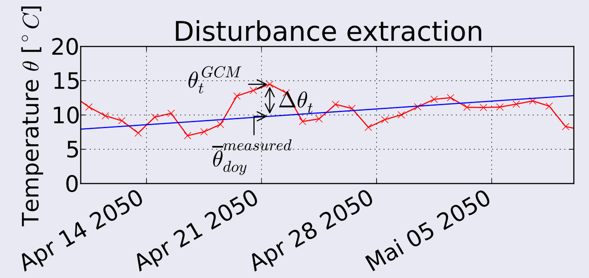


Figure : Extracting the disturbance from bias corrected GCM output.

Simulation with GCM disturbance

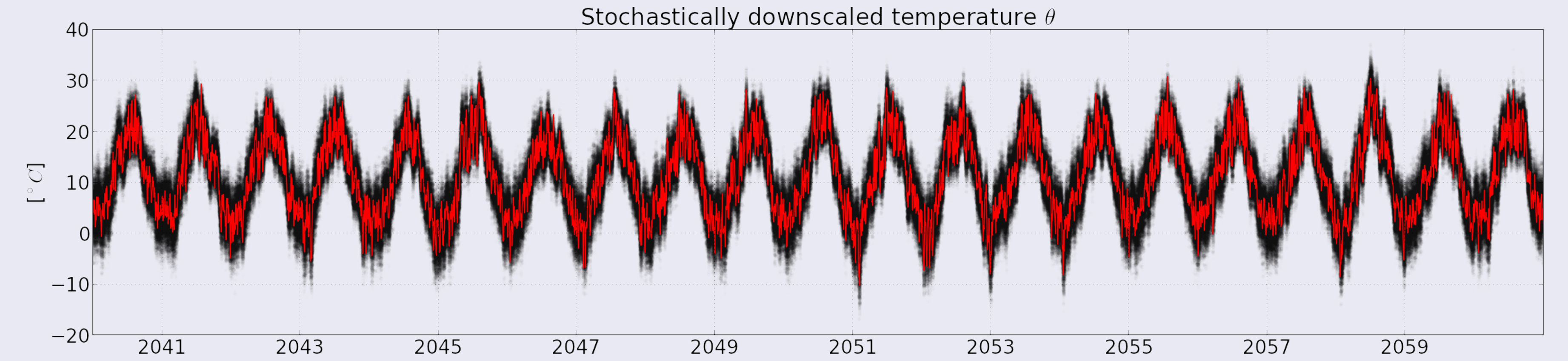


Figure : Recovered variability by the weather generator VG. The red line is bias-corrected GCM output used as disturbance for simulation. Black points are generated from 100 realizations. The GCM data used was MPI/OM ECHAM5 A1B Scenario 2040-2060.

Summary

1. The combination of quantile-quantile transformations and a simple vector autoregressive model resulted in a weather generator able to produce time series sufficiently complex for hydrodynamic and ecological modelling. This setup was made possible by the fact that precipitation was excluded.
2. Introducing a disturbance into the simulation process allows for hand-tailored or GCM driven scenarios.